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Original Research

How Chinese Power Companies Can Effectively Utilize Organizational Resources for a Green and Low-Carbon Transition through Digitalization under the "Dual Carbon" Strategy

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Abstract

The digitalization and green transformation of Chinese power companies are crucial for achieving sustainable development. However, the deep-level impact mechanisms of digitalization on low-carbon transition remain underexplored, especially under the "Dual Carbon" strategy. This study constructs a theoretical model based on the Technology-Organization-Environment (TOE) and Resource Orchestration theories. Using survey data from 371 managers, we employ Partial Least Squares Structural Equation Modeling (PLS-SEM) and Fuzzy-set Qualitative Comparative Analysis (fsQCA) to examine the driving factors and pathways of digitalization's impact on low-carbon transition. The research findings indicate that: (1) Seven categories of resources significantly impact the green and low-carbon transition; (2) Further analysis reveals that the application degree of green low-carbon technologies, relative advantage, green low-carbon transition strategy, and top leadership support serve as mediating resources in digitalization promoting the green low-carbon transition of power companies, with top leadership support being the critical element; (3) Power companies can successfully achieve a green low-carbon transition through three "internal resource-driven" pathways, whereas the lack of policy support is the most critical external factor leading to the failure of the green transition. The findings enhance theoretical research and offer practical insights for policymakers and the power industry on low-carbon transition strategies.

Keywords: digitalization, low-carbon transition, influencing factors, pathways, power companies

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Introduction

Due to the increasing frequency of extreme climate and environmental issues caused by greenhouse gases such as carbon dioxide (CO_2), countries worldwide are becoming more focused on controlling CO_2 emissions and achieving sustainable development [1]. In 2020, global carbon dioxide emissions reached 32.29 billion tons, with energy consumption for power generation and heating accounting for 43% of the total emissions [2]. The power industry, as the largest source of carbon emissions [3], is required to take on greater responsibility for emission reductions [4]. Countries are actively promoting the low-carbon transition of the power industry to mitigate the greenhouse effect, and China is no exception. With rapid economic development, the demand for energy, particularly electricity, is continuously increasing across various industries in China. In 2020, China's total CO_2 emissions were 9.805 billion tons, with 39.6% originating from power generation [5]. As the world's largest producer of electricity and emitter of CO_2, China's power industry faces more stringent carbon reduction requirements [6].

To address the significant challenges of carbon emission reduction, the Chinese government proposed strategic goals of achieving "peak carbon" by 2030 and "carbon neutrality" by 2060 in 2020. Against this backdrop, the power industry is also facing unprecedented pressure for emission reductions and transformation [7]. On the one hand, to respond to the dual carbon strategy, the government has issued a series of policies and regulations to provide institutional guarantees for the green and low-carbon development of the power industry. For example, the impact of the carbon emission trading pilot policy on green innovation in the power industry[8]. On the other hand, the deepening of power market reforms has intensified market competition, forcing traditional power enterprises to accelerate transformation and upgrading to enhance competitiveness. For example, continuous advancements in renewable energy technology and cost reductions have gradually increased the share of clean energy such as wind and solar power in the electricity market [8]. However, due to China's resource endowment of being "rich in coal, poor in oil and gas," the relative maturity of coal-fired power technology, and the limitations of other energy generation [9], it is difficult for the power industry to move away from coal resources in the short term [10]. Meanwhile, the continuous increase in energy demand, particularly for electricity, driven by economic development exacerbates this contradiction [11]. Therefore, traditional power production methods can no longer meet the requirements of the dual carbon strategy, and power enterprises urgently need to achieve sustainable development through technological innovation and changes in management models.

Fortunately, with the continuous emergence of the Fourth Industrial Revolution, digitalization has brought profound changes to various countries and industries worldwide [12]. The increasing contribution of the digital economy to green and low-carbon development [13], has provided an opportunity to address this issue. For example, digital transformation and digital finance have been widely proven to positively impact corporate green innovation, promoting high-quality green development [14, 15]. The power industry is no exception. Digital transformation is considered an effective means to drive changes in production and operations, energy conservation, and the achievement of green and low-carbon transformation. Previous studies have shown that the introduction of digital technology can optimize production and operational activities, management models, and operational mechanisms, thereby enhancing productivity [16]. This is particularly important for energy-intensive and highly polluting industries like the power sector. Wang et al. (2023), through analyzing data from Chinese listed companies, found that digital transformation significantly enhances the green total factor productivity (GTFP) of enterprises, particularly in traditional industries like the energy sector [17]. Digital transformation has provided new opportunities for power enterprises to reduce carbon emissions, achieve green and low-carbon transformation, and pursue sustainable development.

However, despite previous research providing valuable insights into the green and low-carbon transition of the power industry, there are two main limitations: First, previous studies have mainly focused on regional or industrial levels, neglecting the "bottom-up" investigation of influencing factors and mechanisms of energy-saving and carbon reduction at the micro-level of power enterprises. For example, research has primarily focused on calculating and predicting carbon emissions, identifying influencing factors, carbon emission performance, and carbon emission efficiency at various scales [18-20], or analyzing the impact of carbon reduction technologies on the power industry [21]. Second, there is still a lack of research on the impact mechanisms and logical relationships of green and low-carbon transition of power enterprises in the context of digitalization. Especially, the effects of the green and low-carbon transition of power enterprises are influenced by the complex interaction of various internal and external factors, necessitating further clarification of the deep mechanisms of digitalization on internal organizational resources.

Therefore, this study, based on the "dual carbon" strategy, aims to explore the impact of digitalization levels on the green and low-carbon transition of power enterprises, thereby clarifying its internal mechanisms. Furthermore, based on TOE theory and resource orchestration theory, this study reveals the impact of internal organizational resources on green and low-carbon transition, thus uncovering the "black box" of how Chinese power enterprises effectively utilize organizational resources through digitalization to achieve green and low-carbon transition.

Theoretical Framework and Research Hypotheses

Theoretical Framework

To reveal how digitalization achieves the green and low-carbon transition of power enterprises through internal resources, this study employs the Technology-Organization-Environment (TOE) framework to identify internal and external resource elements of the green and low-carbon transition of power enterprises. The TOE framework is a theoretical model that analyzes the influencing factors in the adoption and implementation of new technologies by enterprises, divided into three dimensions: technology, organization, and environment [12]. It has been widely applied in studies on technology-induced organizational change [22]. The digital transformation of power enterprises, as a technological forerunner, orchestrates green and low-carbon resources through the diffusion of green technology innovations, driving green transformation. Therefore, it is necessary to comprehensively evaluate the green and low-carbon transition of power enterprises in the context of digital transformation by integrating resource orchestration theory. The resource orchestration theory is an advancement of the resource-based view (RBV) [23]. Compared to RBV, resource orchestration theory emphasizes that the effective configuration, combination, and utilization of resources and capabilities are essential for gaining sustained competitive advantage [24]. Since the green and low-carbon transition of power enterprises involves complex internal and external factors and their dynamic interactions, merely identifying resource elements is insufficient to reveal the transition mechanisms. Integrating the TOE theory and resource orchestration theory provides an effective analytical framework to uncover how power enterprises utilize organizational resources through digital transformation to achieve a green and low-carbon transition.

Against the backdrop of green and digitalization becoming significant features of economic and social development [25], this study selects the application degree of green and low-carbon technology (AGT) and relative advantage (RA) in the technology dimension, transformation cost (TC), employee engagement (EE), organizational preparedness (OP), green and low-carbon transformation strategy (GTS), and senior leadership support (SSL) in the organization dimension, and competitive pressure (CP) and policy support (PS) in the environment dimension through the TOE framework, considering digital transformation as an important influencing factor. Based on this, this study constructs a research model for the impact mechanisms and implementation paths of the green and low-carbon transition of Chinese power enterprises, as shown in Fig. 1.

Research Hypotheses

Analysis of the Impact of Digitalization

Digital transformation is the product of the mutual promotion of information technology and business innovation, exhibiting significant technological and economic resonance effects [26]. The digitalization

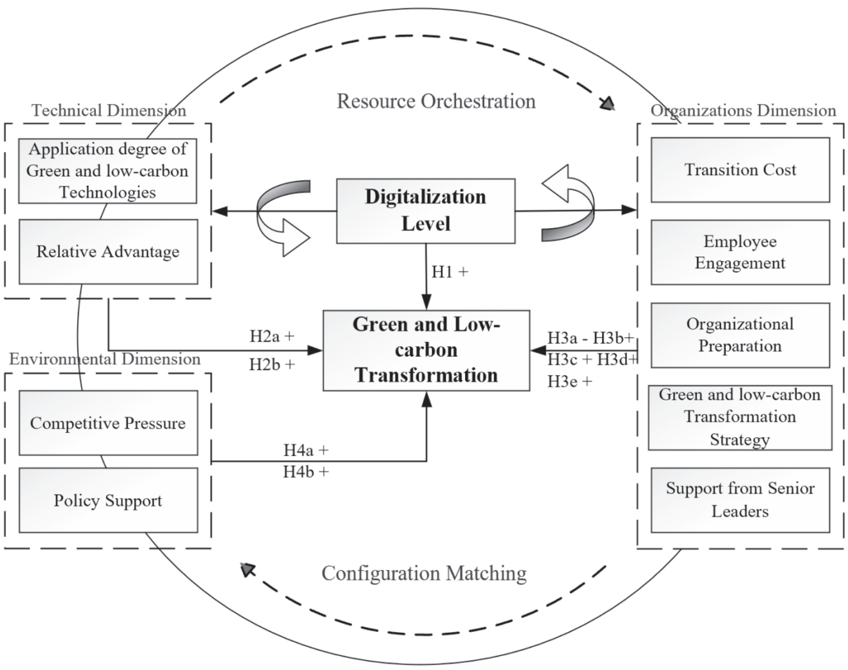

Fig. 1. Research model of the mechanisms for achieving green and low-carbon transition in power companies based on digital transformation.

level of power enterprises refers to the degree of application in information technology, data analysis, and automation. Previous studies have shown that the level of digitalization can influence the strategic implementation of enterprises in various dimensions, such as technology and organization, through the diffusion effect of technological innovation [12], particularly in terms of green and low-carbon transformation. Due to its green attributes, digitalization can promote green and low-carbon development through digital empowerment, which has received widespread attention [27-29]. The green and low-carbon transformation of power enterprises is usually influenced by low-carbon technology [30], and internal and external organizational environments [31]. For example, Shang et al. (2023) found that the level of digital transformation in listed companies significantly reduces carbon emission intensity by enhancing technological innovation, internal control, and environmental information disclosure capabilities [32]. This study measures the degree of digital transformation of power enterprises by their level of digitalization. Based on the above analysis, the following hypothesis is proposed:

H1: The digitalization level of power enterprises positively impacts their green and low-carbon transformation.

Impact of Technological Resources on Green and Low-Carbon Transition

Technological resources are the foundation for driving the green and low-carbon transition of power enterprises. Low-carbon technology, as a key tool for achieving green development, is crucial for power enterprises in reducing emissions [31]. Power enterprises can significantly reduce reliance on fossil fuels, decrease greenhouse gas emissions, and achieve changes in energy structure and operating models by introducing low-carbon technologies such as carbon capture and storage, new fuel power generation, and smart grids [33]. The extent of green and low-carbon technology applications reflects the willingness of enterprises to adopt and practice energy-saving and carbon reduction technologies. Relative advantage is particularly important in the green and low-carbon transition. Enterprises gain comprehensive benefits from the green and low-carbon transition, such as improved cost efficiency, operational effectiveness, market competitiveness, and reduced environmental impact, bringing economic and social responsibility benefits and shaping corporate brand image. Moreover, the digitalization level of power enterprises can enhance the innovation and utilization efficiency of technological resources. For example, Zhang et al. (2023) found that digitalization actively promotes innovation in energy storage technology [34]. Digitalization also guides enterprises to prioritize cost-effective green technologies by improving the accuracy of green technology investment decisions. Data-driven investment decisions not only optimize the allocation of technological resources but also enhance the relative advantage of enterprises in the green and low-carbon transition, accelerating the transformation process. Based on the above analysis, the following hypothesis is proposed:

H2a/H2b: The level of digitalization positively affects the green and low-carbon transition of power enterprises by promoting the application of green and low-carbon technologies and enhancing relative advantage.

Impact of Organizational Resources on Green and Low-Carbon Transition

The green and low-carbon transition involves multiple organizational resource elements, including transition costs, employee engagement, organizational preparedness, transition strategy, and top leadership support. First, the costs of green and low-carbon transition encompass technological upgrades, infrastructure modifications, personnel training, and operational costs. These significant investments may hinder short-term financial performance and adoption willingness [33]. Digitalization, by optimizing energy management and operational processes, can reduce transition costs, improve production efficiency, and decrease labor demand, thus promoting green technology innovation [17]. Second, employees are crucial for driving corporate transformation. Active employee engagement not only enhances the acceptance and implementation of green strategies but also effectively promotes green innovation and environmental management practices by increasing environmental awareness [35]. Digital technologies, such as internal social media, online training systems, and data visualization tools, can enhance employee engagement [36]. Furthermore, good organizational preparedness and a clear green and low-carbon transition strategy are essential guarantees for a successful transition. Organizational preparedness provides foundational support for technology-driven corporate transformation, ensuring a smooth transition [12], while a clear transition strategy offers a defined development direction and specific action guidelines, ensuring effective resource allocation and utilization. Studies have shown that an increased level of digitalization aids in the formulation and implementation of green and low-carbon transition strategies, enhancing the ability of enterprises to address carbon reduction [37].

Finally, support from top leadership is a critical factor in achieving green and low-carbon transition goals. Top leadership support ensures the smooth formulation and execution of transition strategies, providing necessary direction and motivation, promoting the effective allocation of key resources, including technology, capital, and personnel, and shaping a positive corporate culture that motivates employee participation [38]. In this process, digitalization significantly reduces uncertainty and risk during the transition by optimizing decision-making processes, enhancing internal communication and collaboration, and increasing the transparency and traceability of strategy execution [39, 40]. Based on the above analysis, the following hypotheses are proposed:

H3a/H3b/H3c/H3d/H3e: Digitalization positively impacts the green and low-carbon transition of power enterprises by reducing transition costs, enhancing employee engagement, improving organizational preparedness, strengthening transition strategies, and promoting top leadership support.

Impact of Environmental Resources on Green and Low-Carbon Transition

The green and low-carbon transition is significantly influenced by external environmental resources, including competitive pressure and policy support. Competitive pressure is a significant external driver of the green and low-carbon transition for power enterprises. The green and low-carbon transition in the power industry exerts a coercive isomorphism effect on enterprises, forcing them to follow suit to maintain competitiveness. Simultaneously, the increasing market demand for clean energy and low-carbon products directly drives enterprises to adjust their business models to meet this trend [38]. The application of green and low-carbon technologies helps improve energy efficiency and reduce operational costs, providing a competitive advantage. Additionally, enterprises mitigate compliance risks through low-carbon transition and enhance public image through proactive environmental measures [38]. Moreover, policy support plays a crucial role in promoting the green and low-carbon transition of power enterprises. Governments reduce the economic barriers and technical obstacles to corporate transition by formulating and implementing environmental regulations, economic incentives, and technical support policies, providing clear directions and goals for enterprises [41]. Since investing in low-carbon technologies increases corporate costs, governments must create market drivers through carbon trading systems and renewable energy quotas. Economic incentives and environmental standards enhance the attractiveness of low-carbon technology investments for enterprises, driving the green and low-carbon transition [33]. Based on the above analysis, the following hypotheses are proposed:

H4a/H4b: Competitive pressure and policy support positively impact the green and low-carbon transition of power enterprises.

Research Methods and Data

Questionnaire Design

Questionnaire surveys, known for their ease of implementation and scientific validity, have been widely used in studies on organizational innovation induced by digitalization [42], and the power industry is no exception. This study employs a structured questionnaire method to quantify the influencing factors of digital transformation on the green and low-carbon transition of power companies. To ensure the relevance and validity of the research variables and measurement items within the context of this study, we based our questionnaire on established scales from related fields [12], modifying them appropriately to fit the specific context of the green and low-carbon transition in power companies. We also sought advice from industry experts and scholars to adjust and refine the questionnaire items. To ensure the scientific rigor and reliability of the questionnaire, a pre-test was conducted to refine and adjust the measurement items, resulting in the final questionnaire used in this study.

The questionnaire consists of two parts: the first part collects basic information about the respondents, such as gender, age, educational background, work experience, type of employer, and nature of the organization. The second part uses quantitative items to measure the core concepts of the research model across the three dimensions of Technology-Organization-Environment, comprising a total of 42 measurement items. A five-point Likert scale (1=”strongly disagree,” 5=”strongly agree”) was used to assess respondents’ attitudes and perceptions. To enhance participation and data authenticity, the questionnaire was designed to be anonymous to protect participants’ privacy. Before completing the questionnaire, respondents from the relevant industry were first provided with a definition of the green and low-carbon transition in power companies and were informed that the survey results would be used solely for this academic research.

Data Collection

To ensure the scientific validity and reliability of the questionnaire data on factors influencing the green and low-carbon transition of power enterprises, a detailed online survey method was employed. Firstly, the “Wenjuanxing” platform was used to design and distribute the questionnaire. The platform’s effectiveness in data collection has been widely applied in academic research. To enhance the specificity and relevance of the questionnaire data, the survey link was distributed to QQ and WeChat groups and academic forums related to the power industry. Experienced professionals and experts were also invited to participate. Participants came from various regions and different scales of upstream and downstream enterprises in the power industry, including management, technical, and operational personnel, ensuring the sample’s breadth and representativeness. Before completing the questionnaire, participants were introduced to the concept of the green and low-carbon transition in power enterprises and assured of the confidentiality of their responses, with results used solely for academic research.

To ensure the validity and authenticity of the data, three specific questionnaire screening criteria were established. First, questionnaires with excessively short completion times were excluded to ensure respondents had sufficient time to answer thoughtfully. For example, based on the number of items, questionnaires completed in less than one minute were considered insufficiently thoughtful. Second, common sense questions were included to identify and exclude potentially careless respondents who answered these questions incorrectly. Finally, questionnaires with a high repetition rate of answers were excluded to avoid mechanical answering and to ensure analyzable results. Through these screening steps, a total of 371 valid questionnaires were obtained, with an efficiency rate of 80.3%. This sample size meets the minimum sample size requirement of being greater than ten times the number of items in the PLS-SEM model [43], ensuring the reliability of data analysis.

Lastly, the basic characteristics of the respondents are detailed in Table 1, where the gender ratio is balanced, with male and female respondents each constituting around 50%. In terms of educational background, respondents with a bachelor's degree or below accounted for over 80%, while those with a master's degree or above were less than 20%. This phenomenon may reflect the importance of practical experience over academic education in the power industry. Additionally, the age of respondents was mainly concentrated in the 25-30 range, with nearly 60% having less than five years of work experience, indicating a relatively young workforce in power enterprises and high engagement of new employees in the green and low-carbon transition.

Since the data in this study were collected through a questionnaire survey, there is a potential risk of common method bias (CMB) affecting the relationship between independent and dependent variables due to the singularity of the data collection process and tools [44]. To address this issue, we employed the widely used Harman's single-factor test to detect the presence of CMB in the data[44]. The results showed that the largest single factor accounted for only 38.96% of the total variance, which is below the 40% threshold [45].

Analytical Methods

To comprehensively explore the mechanisms by which digitalization affects the green and low-carbon transition of Chinese power enterprises, this study employs both PLS-SEM and fsQCA for two reasons. Firstly, PLS-SEM requires lower distribution and quantity requirements of data and can reveal causal relationships between variables based on small sample sizes by constructing linear combinations of latent variables. It is particularly suitable for complex models composed of multiple constructs [46]. Thus, this method helps in effectively identifying the deep-seated impact mechanisms of digitalization on the green and low-carbon transition of power enterprises based on questionnaire data, specifically the "net effect" of individual influencing factors. Additionally, it reveals the mediating effects of organizational resource elements, ensuring the reliability and validity of the estimated results [47].

Secondly, fsQCA, a set-theoretic method, identifies necessary and sufficient conditions, providing in-depth logical reasoning and qualitative comparative analysis. It analyzes the impact of various combinations

Table 1. Basic characteristics of survey respondents.

Basic Information	Category	Frequency	Percentage (%)
Gender	Male	207	55.80%
	Female	164	44.20%
Education Level	Associate degree or below	116	31.27%
	Bachelor's degree	194	52.29%
	Master's degree	47	12.67%
Age	Doctoral degree	14	3.77%
	<25 years	61	16.44%
	25-35 years	204	54.99%
	36-45 years	68	18.33%
	>45 years	38	10.24%
Work Experience	<3 years	135	36.39%
	3-5 years	89	23.99%
	6-10 years	77	20.75%
	11-15 years	43	11.59%
	>15 years	27	7.28%

of factors on the outcome variable, revealing the "configuration effects" in complex causal relationships [48]. This is particularly suitable for exploring the successful pathways and failure reasons of different condition combinations in the green and low-carbon transition of power enterprises [49]. Through fsQCA analysis, the effective pathways for power enterprises to achieve a green and low-carbon transition under different environmental and resource conditions can be more precisely identified, further deepening the understanding of the internal mechanisms by which digitalization drives corporate green transitions. Therefore, combining these two methods allows for a quantitative analysis through PLS-SEM to understand the independent and joint effects of various factors and a qualitative comparison through fsQCA to identify effective pathways and key conditions under different scenarios, thereby increasing the depth and breadth of the study.

Results

PLS-SEM Analysis

Measurement Model

The evaluation of the measurement model is a critical first step in assessing the quality of the PLS-SEM research model. This study evaluates the model quality from three aspects: reliability, convergent validity, and discriminant validity. First, regarding reliability, Cronbach's α values and composite reliability (CR) values of all measurement variables in this study are greater than 0.7, meeting the required standards [50]. This indicates that the selected measurement variables in this study have good reliability. Second, for convergent validity, the average variance extracted (AVE) is used as the primary assessment metric. The AVE values for all measurement variables in this study exceed the minimum threshold of 0.5 [50], indicating that all variables in the model possess good convergent validity. Lastly, concerning discriminant validity, all variables in this study largely meet the required standards. The evaluation of the measurement model for each variable is shown in Table 2, enabling the subsequent structural model analysis.

Structural Model

This study evaluates the structural model of PLS-SEM using three key indicators: the coefficient of determination (R^2), cross-validated redundancy (Q^2), and effect size (f^2) [51]. First, the coefficient of determination (R^2) represents the amount of variance in the endogenous constructs explained by the exogenous constructs, serving as an indicator of the model's explanatory power. In this study, the R^2 value for Green and Low-Carbon Transition (GLT) is 0.737, and the adjusted R^2 value is 0.729, which exceeds the standard of approximately 0.670 that Chin considers indicative of high explanatory power [51]. This suggests that the model has strong explanatory power for GLT in power companies. Second, the Q^2 value of the structural

Table 2. Reliability and validity indices.

Constructs	Items	Loadings	Cronbach's α	CR	AVE
Application degree of Green and low-carbon Technologies (AGT)	AGT1	0.906	0.811	0.876	0.639
	AGT2	0.762			
	AGT3	0.751			
	AGT4	0.769			
Relative Advantage (RA)	RA1	0.776	0.737	0.835	0.559
	RA2	0.753			
	RA3	0.742			
	RA4	0.718			
Transition Cost (TC)	TC1	0.760	0.828	0.881	0.650
	TC2	0.880			
	TC3	0.812			
	TC4	0.767			
Employee Engagement (EE)	EE1	0.813	0.724	0.845	0.644
	EE2	0.793			
	EE3	0.802			

Organizational Preparation (OP)	OP1	0.781	0.764	0.849	0.585
	OP2	0.749			
	OP3	0.783			
	OP4	0.746			
Green and low-carbon Transformation Strategy (GTS)	GTS1	0.726	0.726	0.829	0.549
	GTS2	0.769			
	GTS3	0.741			
	GTS4	0.727			
Support from Senior Leaders (SSL)	SSL1	0.806	0.830	0.887	0.663
	SSL2	0.807			
	SSL3	0.827			
	SSL4	0.815			
Competitive Pressure (CP)	CP1	0.848	0.769	0.866	0.684
	CP2	0.823			
	CP3	0.809			
Policy Support (PS)	PS1	0.767	0.754	0.844	0.575
	PS2	0.764			
	PS3	0.741			
	PS4	0.761			
Digitalization Level (DL)	DL1	0.795	0.764	0.849	0.585
	DL2	0.781			
	DL3	0.740			
	DL4	0.742			
Green and Low-carbon Transformation (GLT)	GLT1	0.760	0.707	0.820	0.533
	GLT2	0.713			
	GLT3	0.738			
	GLT4	0.707			

model should be greater than 0, with higher Q^2 values indicating greater predictive accuracy of the model. All Q^2 values in this study are greater than 0, meeting the requirements [50], indicating that the model has good predictive relevance. Finally, the effect size (f^2) is used to determine the magnitude of the impact of each path in the model [46]. The effect sizes of Digitalization Level (DL) on AGT, EE, GTS, OP, RA, and SSL are all greater than 0.35, representing high effects, while the effects on GLT and TC are low. Additionally, the impact of all independent variables on GLT is of low effect size, as shown in Table 3. The path coefficient diagram of the research model is illustrated in Fig. 2.

Using the Smart-PLS software, this study estimated the significance levels of the paths through the Bootstrapping method with 5000 resamples[43]. As shown in Table 4, first, DL (Digitalization Level) has a significant positive effect on AGT (Application of Green Technology), RA (Relative Advantage), SSL (Support from Senior Leadership), GTS (Green Transition Strategy), GIT (Green Innovation Technology), OP (Organizational Preparedness), and EE (Employee Engagement) at the 0.01 level. It also has a significant positive effect on GLT (Green and Low-Carbon Transition) and TC (Transformation Cost) at the 0.05 level. Second, based on the TOE framework, except for EE, OP, and CP (Competitive Pressure), which do not have a significant effect on GLT at the 0.05 level, the remaining influencing factors all significantly impact GLT. Among them, TC has a significant negative effect on GLT. Finally, regarding the mediation effects shown in Table 5, DL does not have a significant impact on GLT through EE, OP, and TC. However, internal organizational factors such as AGT, RA, GTS, and SSL partially mediate the significant positive

Table 3. Structural model representation effect size f², predictive relevance, and R square.

Construct	Effect Size f²								Q²	R^2	R² Adjusted
	AGT	EE	GLT	GTS	OP	RA	SSI	TC			
AGT			0.024						0.363	0.589	0.588
CP			0.001								
DL	1.433	0.614	0.021	1.002	1.095	1.248	1.263	0.019			
EE			0.004						0.241	0.381	0.379
GLT									0.382	0.737	0.729
GTS			0.018						0.271	0.500	0.499
OP			0.002						0.300	0.523	0.521
PS			0.017								
RA			0.018						0.305	0.555	0.554
SSI			0.044						0.364	0.558	0.557
TC			0.016						0.009	0.018	0.016

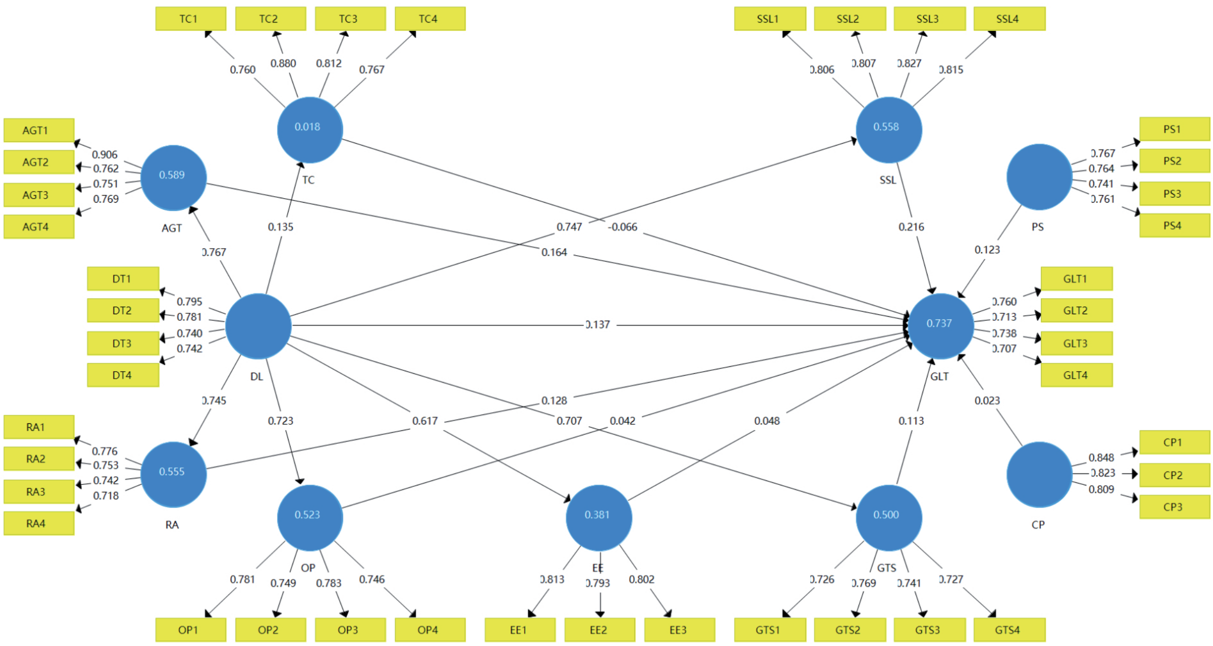

Fig. 2. Path coefficient diagram of the research model.

effect of DL on GLT, with the mediation effect of SSL being the strongest. This indicates that the digitalization level of enterprises plays a crucial role in the support of senior leadership for the green and low-carbon transition.

fsQCA Analysis

Data Calibration

Data calibration is a critical initial step in the fsQCA method, aiming to transform raw quantitative data into fuzzy set membership scores to fit the qualitative comparative logic of this approach. Before conducting fsQCA analysis, each case is assigned a value between 0 and 1, representing the degree of membership in a specific set, typically categorized as "full membership," "crossover point," and "full non-membership" [52]. To ensure the scientific validity and applicability of data calibration, this study considers the specific research context and the actual distribution characteristics of the sample data. The direct calibration method is employed, using the 95th, 50th, and 5th percentiles as anchor points, as commonly used in previous studies [53], to distinguish the degree of membership among samples. Finally, the "calibrate" function in the fsQCA software is utilized to calibrate all raw data.

Table 4. Impact effect results.

Relationship	Path Coefficients	T Statistics	P Values	Result
AGT→GIT	0.164	2.708	0.007	Significant
DT→AGT	0.767	28.378	0.000	Significant
RA→GIT	0.128	2.524	0.012	Significant
DT→RA	0.745	27.786	0.000	Significant
TC→GIT	-0.066	2.05	0.040	Significant
DT→TC	0.135	2.241	0.025	Significant
EE→GIT	0.048	1.117	0.264	Not significant
DT→EE	0.617	15.016	0.000	Supported
OP→GIT	0.042	0.741	0.459	Not significant
DT→OP	0.723	22.737	0.000	Significant
GTS→GIT	0.113	2.437	0.015	Significant
DT→GTS	0.707	23.63	0.000	Significant
SSI→GIT	0.216	3.172	0.002	Significant

Table 5. Hypothesis testing results.

Hypotheses	Relationship	Path Coefficients	T Statistics	P Values	Result
H1	DT→GIT	0.137	2.608	0.009	Supported
H2a	DT→AGT→GIT	0.126	2.733	0.006	Supported
H3a	DT→TC→GIT	-0.009	1.376	0.169	Not Supported
H3b	DT→EE→GIT	0.029	1.094	0.274	Not Supported
H3c	DT→OP→GIT	0.030	0.737	0.461	Not Supported
H3d	DT→GTS→GIT	0.080	2.437	0.015	Supported
H3e	DT→SSI→GIT	0.161	3.122	0.002	Supported
H4a	CP→GIT	0.023	0.515	0.606	Not Supported
H4b	PS→GIT	0.123	2.413	0.016	Supported

Necessity Analysis

In fsQCA, the necessity analysis of antecedent conditions influencing the green and low-carbon transition of power companies is a prerequisite for configurational analysis, used to examine whether a particular condition is a necessary prerequisite for the outcome [54]. First, the necessity analysis calculates the coverage and consistency ratios of conditions. Coverage indicates the proportion of instances where the outcome occurs when the condition is present, while consistency measures the extent to which the outcome occurs whenever the condition is present [52]. As shown in Table 6, under the two configurations of the green and low-carbon transition in power companies, the consistency levels of all individual antecedent conditions are below 0.9, indicating that no single condition sufficiently explains the green and low-carbon transition[53], and none are necessary conditions. This suggests that the green and low-carbon transition of power companies is influenced by the synergistic effects of various conditions, necessitating further configurational analysis.

Configurational Results

After data calibration and necessity analysis, configurational analysis is the core of fsQCA, revealing the complex interactions between variables by identifying different combinations of conditions (i.e., "configurations") that lead to the outcome. Unlike seeking a single optimal solution, configurational analysis emphasizes the existence of multiple possible causal paths. Each configuration is defined by a specific combination of conditions, and each combination

Table 6. Necessity analysis of single conditions.

Conditions	Successfully achieving GLT		Failed to achieve GLT	
	Consistency	Coverage	Consistency	Coverage
AGT	0.792	0.856	0.520	0.456
~AGT	0.496	0.561	0.835	0.765
RA	0.778	0.858	0.505	0.452
~RA	0.503	0.557	0.842	0.755
TC	0.667	0.741	0.611	0.550
~TC	0.595	0.654	0.712	0.634
EE	0.802	0.820	0.567	0.470
~EE	0.481	0.578	0.782	0.762
OP	0.766	0.851	0.516	0.464
~OP	0.517	0.569	0.834	0.743
GTS	0.825	0.821	0.559	0.451
~GTS	0.448	0.556	0.778	0.783
SSL	0.804	0.855	0.525	0.453
~SSL	0.485	0.558	0.832	0.775
CP	0.803	0.822	0.550	0.457
~CP	0.470	0.563	0.786	0.763
PS	0.782	0.861	0.532	0.474
~PS	0.523	0.579	0.844	0.758
DL	0.848	0.841	0.555	0.446
~DL	0.441	0.551	0.801	0.810

logically constitutes a sufficient condition to explain the outcome [55].

First, this study uses the truth table algorithm to identify and simplify the key causal configurations leading to the successful green and low-carbon transition of power companies. This process iteratively simplifies the data to form the simplest expression of condition combinations, collectively constituting multiple possible paths to achieve the specific outcome. To ensure the reliability and interpretability of the combinations, this study sets the frequency threshold for successful green and low-carbon transition cases at 5 and for unsuccessful cases at 6, with a consistency threshold of 0.8, based on previous research findings [55]. By simplifying the logical expressions, the final configurational results of this study are obtained, and predictions are made based on the intermediate and parsimonious solutions.

This study identifies three paths for both successful and unsuccessful green and low-carbon transitions (as shown in Table 7), with overall solution consistencies of 0.981 and 0.970, respectively. The consistency of each combination within the two configurations exceeds 0.9, indicating strong explanatory power for each combination. Additionally, the overall solution coverage for the two configurations is 0.486 and 0.487, respectively, meaning nearly half of the outcomes can be explained by these combinations. For the successful green and low-carbon transition of power companies, besides DL (Digitalization Level), internal organizational factors such as AGT (Application of Green Technology), RA (Relative Advantage), EE (Employee Engagement), GTS (Green Transition Strategy), and SSL (Support from Senior Leadership) are core conditions, which is consistent with the PLS-SEM results. For the unsuccessful green and low-carbon transition configurations, the absence of AGT, RA, EE, GTS, and SSL as core conditions, along with the lack of PS (Policy Support), are significant factors, corroborating the importance of internal organizational factors in both configurations.

To further test the robustness of the configurational results, a stability test was conducted by adjusting the consistency threshold from 0.8 to 0.85. Comparative analysis of the results before and after the adjustment shows consistent findings, indicating the high reliability of the study's results.

Table 7. Green and low-carbon transformation configuration results.

Antecedent condition	Successfully achieving GLT			Failed to achieve GLT		
	S1	S2	S3	F1	F2	F3
AGT	●	●	●	⊗	⊗	⊗
RA	●	●	●	⊗	⊗	⊗
TC	•	•			⊗	⊗
EE	●	●	●	⊗		⊗
OP	•		•	⊗	⊗	⊗
GTS	●	●	●	⊗	⊗	⊗
SSL	●	●	●	⊗	⊗	⊗
CP	•	•	•	⊗	⊗	
PS		•	•	⊗	⊗	⊗
DL	●	●	●	⊗	⊗	⊗
Raw coverage	0.369	0.381	0.449	0.507	0.451	0.446
Unique coverage	0.013	0.025	0.093	0.077	0.021	0.015
Consistency	0.979	0.984	0.987	0.975	0.967	0.967
Overall Solution Coverage		0.486		0.487		
Overall Solution Consistency		0.981		0.970		

Note:● = core condition present. • = peripheral condition present. ⊗ = core condition absent. ⊗ = peripheral condition absent. Blank spaces = condition may be either present or absent.

Discussion

Main Findings

The results indicate that, first, the digitalization level of power enterprises positively impacts the implementation of green and low-carbon transitions (H1). As shown in Table 4, the digitalization level significantly increases the application of green and low-carbon technologies and further enhances the relative advantage of green and low-carbon transitions in power enterprises, with T-values of 28.378 and 27.786, respectively, ranking first and second among all significant influencing resource elements. This indicates that green and low-carbon technologies and relative advantages play key roles in the implementation of low-carbon transitions in enterprises [26, 37]. Furthermore, as shown in Table 5, the digitalization level positively impacts the green and low-carbon transition of power enterprises by enhancing the application of green and low-carbon technologies and relative advantage, indicating partial mediation of these factors in the digitalization process (H2a and H2b). This demonstrates that the impact of digitalization on the green and low-carbon transition of enterprises primarily operates through the promotion of low-carbon technologies and the enhancement of low-carbon advantages.

Previous literature also supports this conclusion, as the role of digitalization in promoting low-carbon transitions has been demonstrated in the manufacturing industry [37]. For example, Hou et al. (2023) found that the digital transformation of the manufacturing industry significantly positively impacts low-carbon technology innovation, serving as a critical driving force for such innovation[26], and the same applies to power enterprises. Particularly in the current context of sustainable and high-quality development, the power industry urgently needs digitalization to drive green and low-carbon transitions.

Subsequently, in the organizational resource dimension, as shown in Tables 4 and 5, although transformation costs have a statistically significant negative impact on the green and low-carbon transition of power enterprises, the hypothesis that digitalization positively affects this transition by reducing costs (H3a) is not supported. Additionally, the digitalization level of enterprises significantly increases green transition costs, which contradicts the theoretical analysis suggesting that digital transformation can reduce these costs. This indicates that, under current conditions, despite efforts by governments and enterprises to promote digital transformation, the green and low-carbon transition remains a financial burden for enterprises, especially in low-carbon technologies [33]. Digitalization has yet to be deeply embedded in production and operations to realize cost efficiencies. Moreover, employee engagement and organizational preparedness do not significantly impact the low-carbon transition of power enterprises and do not mediate the effect of digitalization on this transition; thus, H3b and H3c are not supported. Chen et al. (2024) found that digital transformation positively impacts the carbon performance of industrial enterprises and that talent mediates the relationship between digital transformation and carbon performance, affecting carbon reduction outcomes [56]. Therefore, compared to general employee engagement, low-carbon talent with specific skills and awareness may play a more crucial role in the low-carbon transition of power enterprises. The insignificance of organizational preparedness may be due to the disruptive nature of green and low-carbon transitions on existing organizational structures, which forces changes in established behavioral patterns, thus creating potential obstacles and reducing the positive impact of organizational preparedness on the transition. This phenomenon has also been observed in the digital transformation of construction enterprises [12]. Regarding green and low-carbon transition strategies and top leadership support, H3d and H3e are both supported. Notably, H3e has the highest T-value of 3.122 among all ten hypotheses. This indicates that top leadership support plays the most critical role in digitalization, promoting the green and low-carbon transition of power enterprises. Sheng et al. (2021) also found that the ambivalence of CEOs can weaken the impact of digital transformation on the low-carbon operational management practices of enterprises [39].

Finally, in the external environmental resources dimension, competitive pressure does not significantly impact the green and low-carbon transition of power enterprises, and H4a is not supported. However, policy support has a significant positive impact on the green and low-carbon transition of power enterprises, supporting H4b. The possible reason is that China's power enterprises are government-affiliated with low levels of market competition. Compared to market regulation, government macro-guidance and policy directives are the key drivers for the green and low-carbon transition of power enterprises [57]. The government can guide or encourage relevant low-carbon practices in enterprises through various policies in the power and carbon markets, such as peak-valley electricity pricing, carbon emission trading rules, and carbon emission quota allocation rules [33].

Based on the above analysis, it can be found that although the PLS-SEM method reveals the impact of different resource elements on the green and low-carbon transition, particularly the mediating effects of digitalization in promoting the green and low-carbon transition of power enterprises, it still does not clearly answer how digital transformation interacts through these different resource elements to achieve the green and low-carbon transition of power enterprises. Therefore, it is necessary to discuss the green and low-carbon transition from the perspective of configuration matching based on resource orchestration theory. The configuration results indicate that three paths (S1, S2, and S3) can successfully achieve the green and low-carbon transition of power enterprises, all driven by internal resources (Table 7). Specifically, in addition to the application of green and low-carbon technologies, relative advantage, green and low-carbon transition strategy, top leadership support, and digitalization level, employee engagement is also a core condition in all three paths. This indicates that although employee engagement does not significantly impact the green and low-carbon transition of power enterprises or mediate the relationship between digitalization and the green and low-carbon transition, it remains a core condition from the configuration perspective.

Furthermore, this suggests that under the joint interaction of internal and external resource elements, employees, as the fundamental human resources of enterprise productivity, their level of engagement in the low-carbon transition remains an indispensable resource element for achieving a green transition. The degree of employee engagement reflects their sense of corporate identity and value regarding green and low-carbon transition efforts, thereby affecting the implementation of various green and low-carbon transition tasks. Previous studies have also indicated this situation [56]. Secondly, in the three paths that successfully achieve the green and low-carbon transition of power enterprises, the resource elements of transformation costs, organizational preparedness, competitive pressure, and policy support are marginal or potentially absent. This indicates that internal resource elements are particularly important for a successful green and low-carbon transition, with the application of low-carbon technologies and top leadership support often being key [58].

In the three paths where the green and low-carbon transition of power enterprises was not successfully achieved (F1, F2, and F3), it can be seen that besides the absence of core internal resource elements, the lack of policy support is a key factor leading to the failure of the green and low-carbon transition. Since current green and low-carbon transitions are more about fulfilling corporate social responsibility and responding to calls for action, it is difficult to bring economic benefits to enterprises in the short term [59]. Especially for state-owned power enterprises, without policy support, it is challenging for enterprises to have the motivation and willingness to proactively engage in green and low-carbon transitions [31], which is consistent with the previous conclusions from the PLS-SEM analysis. Therefore, the successful green and low-carbon transition through digitalization often depends on internal leadership support and the deep application of technology. Without policy support and encouragement, the green and low-carbon transition is unlikely to be achieved.

Research Implications

The research findings provide crucial insights for government policy-making. The government should enhance the promotion and support of digital technologies in the power industry, formulating policies to encourage investment and application of digital technologies. Measures may include financial subsidies, tax incentives, and low-interest loans to reduce digital transformation costs. Additionally, improving digital infrastructure, especially in remote and resource-scarce areas, ensures balanced development of digital transformation among power enterprises. Strengthened supervision and guidance should ensure the application of digital technologies aligns with national green and low-carbon development goals and environmental standards. The government should improve and optimize carbon market mechanisms by formulating flexible and effective carbon trading rules and quota allocation systems, encouraging carbon reduction through technological innovation, enhancing the economic benefits and sustainability of the green and low-carbon transition, and ensuring equitable benefits from digital transformation.

Industry stakeholders, particularly top leaders, should recognize the importance of digital transformation in achieving green and low-carbon development and actively implement digital strategies with the necessary resources. Enterprises should invest in low-carbon technology innovation, introducing advanced digital technologies to enhance their application and relative advantage, thus boosting market competitiveness. Employees, as key resources for the green and low-carbon transition, should receive training and incentives to enhance their low-carbon awareness and skills, boosting participation and creativity. Additionally, power enterprises should collaborate with the government, academia, and non-governmental organizations to advance green and low-carbon technology research and application. Participating in government green policy and industry standard formulation allows enterprises to gain policy support and establish a green development benchmark. Finally, investors should focus on and invest in enterprises with strong digitalization and green and low-carbon transition prospects for long-term returns.

Conclusions

With digitalization and greening becoming mainstream, traditional power enterprises urgently need to transition to green and low-carbon practices to address the escalating climate crisis and achieve sustainable, high-quality development. This study first identified ten internal and external organizational resource elements that might affect the green and low-carbon transition of power enterprises based on the TOE framework. Combined with resource orchestration theory, a research model for the green and low-carbon transition of power enterprises driven by digital transformation was constructed. Next, PLS-SEM was employed to analyze nine types of green and low-carbon resources, revealing that seven significantly impact the green and low-carbon transition. Further analysis revealed that four internal organizational resource elements—green and low-carbon technology application and relative advantage in the technical resource dimension, and green and low-carbon transition strategy and top leadership support in the organizational resource dimension—mediate the effect of digitalization on the green and low-carbon transition of power enterprises. Among these, top leadership support is the key resource element. Finally, using fsQCA to orchestrate ten types of green and low-carbon resources, it was found that power enterprises can achieve green and low-carbon transitions through three "internal resource-driven" paths. The failed green and low-carbon transition paths revealed that the lack of policy support often leads to transition failure. In the Chinese context, external policy support and assistance are crucial for the success of green and low-carbon transitions. This addresses the challenge of how power enterprises can leverage green and low-carbon resources to achieve low-carbon transitions in a digitalization context.

This study has some limitations that need to be addressed in future research. Firstly, the PLS-SEM and fsQCA methods selected in this study are limited by the data sourced from questionnaires, which may be subject to respondent bias and may not fully reflect the actual green and low-carbon practices of enterprises. Future research could consider using panel data from publicly listed companies or statistical yearbooks to enhance the comprehensiveness and reliability of the study. Additionally, while this study used the TOE framework and resource orchestration theory, future studies could incorporate theories from other fields for broader insights. Finally, due to the differences in economic development levels, energy structures, and environmental regulations across regions, future research could explore transformation paths from a regional differences perspective.

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Conflict of Interest

The authors declare no conflict of interest.

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